Increasing Object-Level Reconstruction Quality in Single-Image 3D Scene Reconstruction

Anna Ribic Antonio Oroz Meikel Kokowski Franz Srambical
Technical University of Munich
{firstname}.{lastname}@tum.de

Abstract

1. Introduction

While humans can easily infer the 3D structure as well as the complete (panoptic) semantics of a scene from a single image, this task has been a longstanding challenge in the field of computer vision. The task fundamentally prerequisites learning a strong prior of the 3D world. Traditional methods have made significant strides, from generating geometrically coherent structures [10, 37] to learning different instance semantics [16, 23, 32]. More recent approaches directly learn the 3D panoptic semantics as a whole [7, 47], yet they fall short in capturing the intricate details and nuances at the object level. This paper introduces a novel approach to bridge this gap by integrating a specialized object-level model into the reconstruction process, thereby leveraging the specialized model's object-priors.

Our approach models panoptic 3D reconstruction as a two-stage problem. We first use the model of Dahnert et al. [7] to create an initial reconstruction. Then, we leverage the instance masks to extract the object geometries out of the reconstructed scene. We input each of the extracted objects along with cropped images from the scene and text labels into a diffusion model [5] to refine the rough object-level geometries. Finally, we integrate the refined object geometries back into the initial scene reconstruction to obtain a complete and refined panoptic 3D scene reconstruction.

In summary, our main contributions are as follows:

- We propose a novel approach to panoptic 3D reconstruction involving an inference pipeline that leverages object-level reconstruction models to refine the output of a 3D scene reconstruction backbone.
- We qualitatively demonstrate the effectiveness of our approach on the 3D-Front [14] dataset, showing significant improvements over the state-of-the-art.
- We show that fine-tuning SDFusion [5] on the input scene's object distribution (in our case the 3D-Future dataset [15]) significantly improves the quality of the refined objects.
- We propose *weighted masking*, a novel technique to integrate masking uncertainty into the object-level reconstruction process.
- We introduce a conceptually simple yet effective method for shape alignment, which outperforms rigid alignment methods in our experiments.
- We openly release our model code, training and inference pipelines, as well as our newly constructed variation of the 3D-Front dataset to facilitate future research in the field.

2. Related Work

2D panoptic segmentation 2D panoptic segmentation merges semantic and instance segmentation, providing detailed pixel-level parsing of images, capturing both general categories (semantic segmentation) and individual object identities (instance segmentation) [21]. Since the original task formulation by Kirillov et al. [21], a number of works have been proposed to solve the task [2–4, 22, 24–26, 31, 40, 41, 44–46], while more recent approaches [20] try to unify image segmentation in its entirety.

Single-view 3D reconstruction The work by Snavely et al. [38] was the first notable attempt at reconstructing 3D scenes from unordered photo collections. Since then, the field of image-based 3D reconstruction has seen a number of advancements, culminating in the task of single-view 3D reconstruction [6, 10, 19, 29, 32, 37, 42].

Shape priors Wu et al. [43] note that the task of single-view 3D reconstruction is non-deterministic, as there are many 3D shapes that can explain a given single-view input, and propose to use shape priors to shape the solution space such that the reconstructed shapes are realistic, but not necessarily the ground truth.

3D scene understanding The task of 3D scene understanding and panoptic reconstruction is analogous to its 2D counterpart and aims to infer the 3D structure and semantics of a scene, including the 3D layout, object instances, and their 3D shapes from images [7] or noisy geometry [17, 18]. Dahnert et al. [7] propose a method – henceforth called *Panoptic 3D* – to jointly solve the tasks of 3D scene understanding and single-view 3D reconstruction by lifting features produced by a 2D backbone into a 3D volume of the camera frustrum, and jointly optimizing for geometric reconstruction as well as semantic and instance segmentation.

Modality-conditioned shape generation 3D generative models represent objects in a variety of modalities, including point clouds [1, 28], occupancy grids [29], meshes [30], and signed distance functions [34]. Furthermore, these models can also be distinguished by the type of input they take, such as incomplete shapes [9], images [13], text [27, 48], or other modalities [49]. Notably, Cheng et al. [5] propose *SDFusion*, a 3D object reconstruction method conditioned on images, text and geometrical input.

Datasets Notable datasets in the field of panoptic 3D reconstruction include ScanNet [8] and Replica [39], which provide rich annotations for scene understanding tasks. Another such dataset, 3D-Front [14], provides comprehensive coverage of indoor scenes while offering detailed geometric reconstructions as well as semantic and instance segmentation annotations. The synthetic 3D dataset contains 6,801 mid-size apartments with 18,797 rooms populated by 3D shapes from the 3D-Future [15] dataset. The dataset's high-quality data acquisition process ensures accurate representations, establishing it as a valuable resource for advancing research in 3D panoptic reconstruction.

In an effort to refine the panoptic reconstruction model, we compiled a custom dataset comprising over 18,000 samples. Leveraging the diverse scenes of the 3D Front dataset, we use BlenderProc [11] for randomly sampling camera poses and 2D rendering. Utilizing a C++ pipeline from Dahnert et al. [7], we generate annotated 3D geometry within the respective camera frustum

3. Method

We leverage Panoptic 3D [7] to predict the camera frustum geometry and associated 3D semantic and instance labels within the image. This model provides us with both 2D and 3D representations of detected objects. To achieve this, Panoptic employs a ResNet-18 encoder for feature extraction from the input image. Subsequently, these features are utilized to predict both a 2D depth map and 2D instance mask through a depth encoder and a Mask R-CNN applied directly to the ResNet-18 features.

During training we learn the 2D output utilizing a proxy loss for both depth estimation and instance segmentation.

Our panoptic 3D reconstruction is trained to predict geometry, semantic labels, and instance ids for sparse voxels within the truncation region. For the geometric loss Lh g , each hierarchy level is trained to predict geometry occupancy using a binary cross entropy loss, and the final hierarchy level also

The depth map facilitates the backprojection of features into a sparse volumetric grid, and the 2D instance mask is propagated to serve as a seed for the 3D instance mask prediction. Finally, a U-Net architecture processes the sparse backprojection to forecast occupancy, distance field, and both semantic and instance labels for each individual occupancy within the grid.

To learn the 3D reconstruction, we utilize a binary cross entropy loss for the occupancy prediction at different hierarchy levels and the l1 loss for the distance field on the final hierarchy level. The total loss can be formalized as:

$$\mathcal{L} = w_d\mathcal{L}_d + w_i\mathcal{L}_i + \sum_h (w_g\mathcal{L}_g^h + w_s\mathcal{L}_s^h + w_o\mathcal{L}_o^h), \quad (1)$$

with

$$\mathcal{L}_d \quad (2)$$

representing the 2D depth estimation loss,

$$\mathcal{L}_i \quad (3)$$

the 2D instance segmentation loss and

$$\mathcal{L}_g^h, \mathcal{L}_s^h, \mathcal{L}_o^h \quad (4)$$

represent the geometry, 3D semantic label and 3D instance loss at different hierarchy levels.

For each detected object, we use the 2D instance mask to extract RGB crops of the input image, and the 3D instance mask to extract the corresponding 3D geometry. The extracted geometry along with the semantic label are subsequently input into the SDFusion model for shape reconstruction. The output shape can be formalized as follows:

$$\mathbf{X}P = \Theta_s \circ \mathrm{Concat} \circ \Theta 3D \circ \mathrm{Lift}\left(\Theta_i, \mathrm{Depth}, \mathrm{Seg}\right)(I) \quad (5)$$

Where:

- I is the input RGB image.
- Θ_i represents the 2D backbone (e.g., ResNet-18) encoding of I.
- $\mathrm{Depth}(I)$ denotes the depth estimation from the encoded image.
- $\mathrm{Seg}(I)$ represents the instance segmentation (e.g., Mask R-CNN) of I.
- $\mathrm{Lift}(\cdot)$ function lifts 2D features to 3D using the camera intrinsics, depth estimates, and 2D instance segmentation, resulting in a sparse 3D feature volume.

- Θ_{3D} involves the back-projection and encoding of lifted features into a common space using sparse 3D convolutions.
- Θ_s denotes the sparse 3D encoder (e.g., a UNet-style architecture) that processes the concatenated features to produce the final panoptic 3D scene reconstruction.

SDFusion [5] utilizes a signed distance field as its primary input and, additionally leverages an RGB image and a textual representation as conditional inputs to guide the reconstruction process. To this end, SDFusion employs task-specific encoders ([12, 35]) to process the 2D image and text embeddings, while simultaneously embedding the 3D shape into a latent space using a pre-trained vector quantized variational autoencoder (VQ-VAE) [33]. Noise is then introduced to the shape latent via forward diffusion, which is followed by a concatenation of the conditional embeddings. This serves as input to the 3D U-Net [36] denoising network which reconstructs the latent code. Within the denoising U-Net, cross-attention is applied along the concatenated latent code to modulate the denoising process. Ultimately, the VQ-VAE decoder reconstructs the shape.

The output of SDFusion is front-facing and might not align with the object's orientation in the reconstructed 3D scene. To address this, we employ a registration algorithm to ensure proper alignment of the reconstructed objects within the scene. This process consists of 3 key steps:

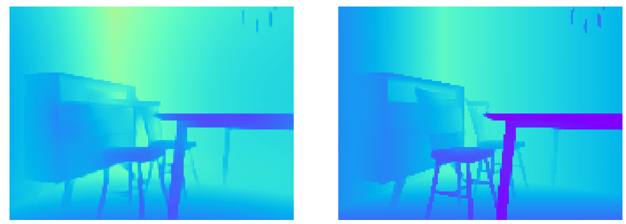
1. **Floor Alignment:** To establish a common reference frame and facilitate subsequent orientation, we align the reconstructed object with the floor plane of the 3D scene.
2. **Rotational Optimization:** Following floor alignment, the object is systematically rotated through 16 discrete, uniformly distributed positions around its y-axis. This exploration covers a diverse range of potential orientations.
3. **Selection based on Similarity:** The final step involves selecting the orientation that minimizes the per-point difference between the reconstructed object (mesh) and the corresponding elements within the scene (point) utilizing [**?**]. This metric serves as a quantitative measure of alignment accuracy.

4. Results

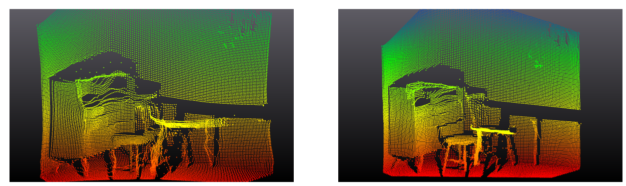
Our study demonstrates the efficacy of our methodology in enhancing the visual presentation of objects within 3D reconstructions. As depicted in Figure 1, the unprocessed Panoptic reconstruction exhibits visual artificats and irregularities, while our approach yields smoothed surfaces, facilitating improved recognition through visual observation. Additionally, we observe the sensitivity of our alignment procedure to the instance masks generated by Panoptic. Although the predicted objects maintain smoothness (likely due to the conditioning in SDFusion), our alignment algorithm occasionally results in object intersection, as illustrated in Figure 2.

	Depth	Box Class.	Box Regress.
Panoptic	0.222	3.461	0.09
Ours	0.196	1.958	0.183

Table 1. Results for joint training of the 2D encoder, depth estimation and 2D instance prediction. For depth we report the ℓ_1 distance between the predicted and ground-truth depth maps. Additionally we report the ℓ_1 distance for the regressed 2D boxes and a CE-loss on the box classification.



Depth Map



Geometry from Depth

Figure 1. 2D panoptic results. Ours vs. Dahnert et al. [7]

Panoptic Reconstruction We leverage our synthesized dataset to refine the training of the panoptic reconstruction model proposed by Dahnert et al. [7]. Initially, we pretrain the 2D encoder, depth estimation and 2D instance prediction with an ADAM optimizer using a batch size of 1 and learning rate 1e-4 for 570k iterations.

The evaluation results for our 2D model compared to the pre-trained model from Dahnert et al. [7] are presented in Tab. 1. As depicted in Fig. 1, our approach demonstrates comparable performance to the pre-trained model but still struggles to produce clean depth results, exhibiting certain irregularities.

Despite our efforts, limitations such as time constraints and the relatively small size of our dataset hindered our ability to train a 3D model that achieves performance on par with the pre-trained counterpart. We outline potential directions for future work in this regard.

5. Limitations

We conducted separate training for both the Panoptic model and the SDFusion model. To increase the performance we advocate for an end-to-end training approach. Given that the Panoptic model outputs occupancies and a distance field in terms of geometry, a differentiable transformation to a signed distance field is necessary to allow end-to-end training. This integration would enable SDFusion to effectively backpropagate gradients and directly learn from SDFusions noisy inputs. Another constraint lies in our registration algorithm, which selects one out of 16 predefined positions, which can pose a challenge in achieving perfect alignment relying on the initial orientation of the reconstructed objects. A more robust alignment strategy can enhance the overall quality of the final scene.

6. Conclusion

In summary, our methods has demonstrated the efficacy of employing a reconstruction and a diffusion model to enhance aesthetic quality of visual scenes. This approach can be a powerful tool to elevate the immersive experience such as in virtual reality and augmented reality. Our findings underscore the potential of our method and can serve as a starting point for future research to further increase the quality and alignment of the reconstructed objects.

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